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Hybrid multi-objective evolutionary algorithms based on decomposition for wireless sensor network coverage optimization

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ABSTRACT

In Wireless Sensor Networks (WSN), maintaining a high coverage and extending the network lifetime are two conflicting crucial issues considered by real world service providers. In this paper, we consider the coverage optimization problem in WSN with three objectives to strike the balance between network lifetime and coverage. These include minimizing the energy consumption, maximizing the coverage rate and maximizing the equilibrium of energy consumption. Two improved hybrid multi-objective evolutionary algorithms, namely Hybrid-MOEA/D-I and Hybrid-MOEA/D-II, have been proposed. Based on the well-known multi-objective evolutionary algorithm based on decomposition (MOEA/D), Hybrid-MOEA/D-I hybrids a genetic algorithm and a differential evolutionary algorithm to effectively optimize sub-problems of the multi-objective optimization problem in WSN. By integrating a discrete particle swarm algorithm, we further enhance solutions generated by Hybrid-MOEA/D-I in a new Hybrid-MOEA/D-II algorithm. Simulation results show that the proposed Hybrid-MOEA/D-I and Hybrid-MOEA/D-II algorithms have a significant better performance compared with existing algorithms in the literature in terms of all the objectives concerned.

1. Introduction

Wireless Sensor Networks (WSNs) are self-organized networks consisting of sensor nodes capable of sensing, processing and wireless communication. Coverage control is a crucial issue in WSN, which mainly concerns how well a sensor network monitors a field with proper node deployment [1–3]. The energy of sensor nodes, the network communication bandwidth and the computing ability are generally limited resources, and thus the coverage sustainability in WSNs cannot always be guaranteed. How to balance the network energy consumption to prolong network lifetime while maintaining a high coverage rate is an important issue, which can be modeled as a multi-objective optimization problem (MOP) [4,5].

The goal to solve MOPs with two or more conflicting optimization objectives is to calculate an approximation of the Pareto Front. MOPs should be provided with multiple non dominated solutions concerning different objectives, which are difficult to be optimized if been converted into a single combined objective. Kulkarni et al. [6] used computational intelligence and evolutionary algorithms to solve MOPs of coverage control in WSN in complex and dynamic environments. Ozturk et al. [7] obtained better dynamic deployments for WSN by using an artificial bee colony algorithm. Kulkarni et al. [8] applied particle swarm optimization (PSO) to address issues such as optimal deployment, node localization, clustering, and data aggregation in WSN. It is shown that PSO is a simple, effective and efficient algorithm. Özdemir et al. [9] modelled the WSN coverage control problem as a MOP problem with two objectives: the coverage rate and the network lifetime. The multi-objective problem is then converted into a series of single objective sub-problems, each solved by a genetic algorithm. Experimental results showed that the proposed MOEA/D algorithm outperformed an improved non-dominated sorting genetic algorithm (NSGA-II) [10]. Shen et al. [11] proposed a MOEA/D-PSO algorithm by considering two optimization objectives including coverage rate and network lifetime, and applied a particle swarm optimization algorithm in MOEA/D. Since the balance of energy consumption has a great impact on the entire network, the energy equilibrium [12] is thus added as another objective in this research.

Hybrid algorithms and improved particle swarm optimization algorithms have been well applied in other fields. Xu et al. [13] proposed a new hybrid evolutionary algorithm to solve multi-objective multicast routing problems in telecommunication networks. The

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algorithm combines simulated annealing based strategies and a genetic local search to effectively find more non-dominated solutions. Experimental results demonstrated that both the simulated annealing based strategies and the genetic local search can efficiently identify high quality non-dominated solution sets for the problems and outperform other conventional multi-objective evolutionary algorithms. In a novel PSO algorithm based on the jumping PSO (JPSO) algorithm developed by Xu et al. [14], a path replacement operator has been used in particle moves to improve the positions of the particles with regard to the structure of the routing tree. The experimental results demonstrated the superior performance of the proposed JPSO algorithm over a number of other state-of-the-art approaches.

Based on the above analysis, this paper considers the multi-objective coverage control optimization problem in WSN with three objectives, including the energy consumption, the coverage rate and the equilibrium of energy consumption. We propose two improved multi-objective algorithms, namely Hybrid-MOEA/D-I and Hybrid-MOEA/D-II. In order to diversify the search, two reproduction operators based on Genetic Algorithm (GA) and Differential Evolution (DE) have been hybridized in Hybrid-MOEA/D-I to obtain a better Pareto solution set. A weight is also set for each objective to guide the search direction. To further enhance the search ability of Hybrid-MOEA/D-I and preserve high quality individuals in each generation, a new Hybrid-MOEA/D-II algorithm is devised to integrate an improved discrete binary particle swarm optimization algorithm in [15] as the enhancement strategy to obtain a better Pareto solution set. An extensive set of experiments have been carried out to systematically investigate the performance of our proposed algorithms.

The remainder of the paper is organized as follows. Section 2 gives the definition of the multi-objective coverage control optimization problem. Section 3 provides the summary of the related works of the multi-objective coverage optimization problem in WSN. We describe our proposed Hybrid-MOEA/D-I and Hybrid-MOEA/D-II algorithms in Section 4. Experimental results are reported in Section 5. The conclusion and some future work are given in Section 6.

2. The multi-objective coverage optimization (MCO) problem

In WSN, coverage problems can be divided into face coverage, line coverage and target point coverage. In this paper, we use the target point coverage, refers to the target point at any time by one or more than one sensor node coverage. Assume the target field D is a two-dimensional square, the targeting point $S_T = \{t_1, t_2, \ldots, t_M\}$, $t_j = (x_j, y_j)$ are randomly distributed in D, M is the number of target points, $j \in [1, \ldots, M]$, x_j and y_j are the coordinates of each target point. A set of sensor nodes S is randomly deployed over D where $S = \{s_1, s_2, ..., s_n\}$, $s_i = (x_i, y_i, r_i)$, n is the number of sensor nodes, $i \in [1, ..., n]$, x_i and y_i are the coordinates of each sensor node, and r_i is the maximum ideal sensing radius of sensor node s_i. We assume the Sink node has unlimited energy supply and each sensor node has the same physical structure, thus the communication ability, the initial energy and the computing power of each sensor node are the same. If the sensor node's energy is exhausted then this is not working, we call the node for the dead node. The Sink node or each sensor node can get its own location information and communicate with its neighboring nodes. In Fig. 1, randomly deployed sensor nodes (red nodes) and targeting points (blue nodes) are showed within a two-dimension square, X axis and Y axis represent the horizontal and the vertical coordinate, respectively. The yellow triangle in the center is the Sink node. The coverage field of s_i at position (x_i, y_i) is indicated by the green circle area with a radius of r_i.

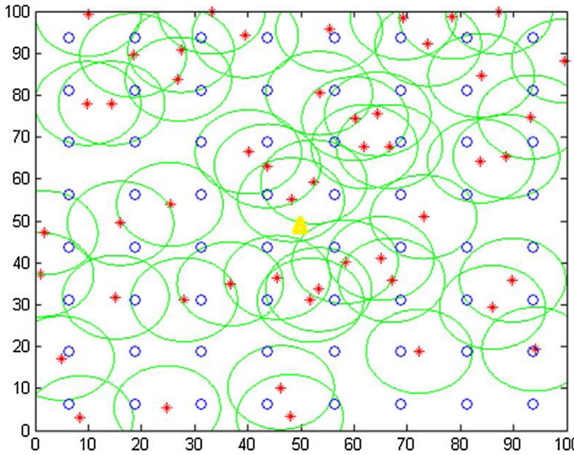


Fig. 1. Wireless Sensor Network with Random Nodes Deployment.

2.1. The network model of WSN

In this paper, we adopt the well-known LEACH (Low Energy Adaptive Clustering Hierarchy) routing protocol for WSN as proposed by Heinzelman et al. [16]. The LEACH clustered routing protocol uses rounds to represent the network life. Each round begins with the optimizer method to select the deployment solution, a set-up phase is applied when the clusters are organized, then a steady-state phase is followed when data is transferred from the nodes to the cluster head and finally to the Sink node. The role of the cluster head node is to collect the information of the sensor nodes in the cluster, and then sends the data to the Sink node. The probability of each sensor node being selected as a cluster head is p_c. Each non-cluster head node firstly calculates the energy consumption to communicate with all cluster heads, and then chooses its own cluster head with the lowest energy consumption. In order to balance the energy consumption, cluster head nodes are cyclically changed in each round based on a threshold value $H(i) \in [0, 1]$ given by Eq. (1). If a randomly generated value is less than $H(i)$ then the node becomes the cluster head node in the current round.

$$H(i) = \begin{cases} \dfrac{p}{1 - p \times (r \bmod \dfrac{1}{p})} & if\ \mathrm{i} \in \mathrm{G} \\ 0 & otherwise \end{cases} \tag{1}$$

p is the desired percentage of cluster head nodes in the sensor population, i represents the i-th node, r is the current round number, and G is the set of nodes that have not been selected as the cluster head in the last $1/p$ rounds.

Based on the above definition, WSN can be defined as a two-dimension network with three layers as shown in Fig. 2. At the bottom layer, the sensor nodes are distributed in the targeting area with *num* clusters, where each cluster has *Ks* sensor nodes. Each sensor node can communicate directly with its cluster head. The middle layer is composed of all cluster heads, which can directly communicate with the Sink node at the top layer.

The Euclidean distance between sensor node s_i and the targeting point t_j at position (x_j, y_j) in D is:

$$d(s_i, t_j) = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \tag{2}$$

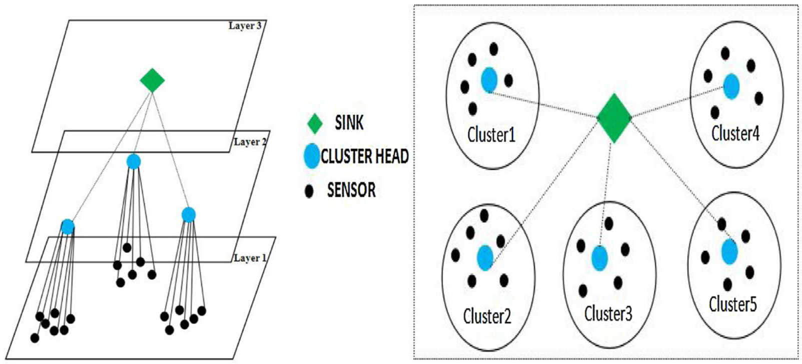


Fig. 2. The WSN Network Model with the Three Layers Structure.

The probability of s_t being covered by s_i is:

$$p(s_i, t_j) = \begin{cases} 0 & r_i \le \mathrm{d}(s_i, t_j) \\ e^{-\lambda \times \frac{d(s_i, s_t) - r_i - r_e}{r_i - d(s_i, s_t)}} & r_i - r_e < \mathrm{d}(s_i, t_j) < r_i \\ 1 & r_i - r_e \ge \mathrm{d}(s_i, t_j) \end{cases} \tag{3}$$

Where r_e is the sensing error of a sensor node, r_i is the maximum ideal sensing radius of a sensor node, and λ is the sensing attenuation coefficient. As long as the target point t_j is covered by at least one active sensor node, it is considered to be covered by the sensor network. Thus the probability p_t of the target point s_t covered by the network is defined as:

$$p_t = 1 - \prod_{i=1}^{n} (1 - p(s_i, t_j)) \tag{4}$$

2.2. The definition of the multi-objective coverage optimization (MCO) problem

In the literature, intensive researches have been carried out on energy efficient routing protocols [18–25] and node placement strategies [26–30] to reduce energy consumption for WSN. Early work often models the optimization problem with a single objective. Recently, the coverage optimization problem [31–37] in WSN has been modeled as a MOP. A MOP is composed of multiple conflicting objectives, and the performance improvement of one objective may cause the performance reduction of one or more other objectives.

The MCO problem concerned in this paper is to schedule sensor nodes in WSN, aiming to select appropriate nodes as cluster head nodes, active nodes and inactive nodes, so that more target points are covered and the energy of the whole network is saved and balanced. Assuming I is a solution of node scheduling for sensor nodes in WSN, we define the following three objectives in the MCO problem.

1) The Energy Consumption

Energy consumption $E(I)$ is the total energy consumed for transmitting, receiving, aggregating signals and activating sensors for solution I, as defined in [17], formulation given in Eq. (5).

$$E(I) = (\sum_{i=1}^{num} \sum_{s \in c_i} E_{s,\ CH_i} + E_{RX} + E_{DA}) + \sum_{i=1}^{num} E_{CH_i,\ Sink} + E_{total} \tag{5}$$

Where num is the number of clusters, c_i is the i-th cluster. CH_i represents the i-th cluster head (CH) node in solution I, which is represented as a fixed-length list of genes of size equal to the total number of nodes in the WSN. The allele of each gene can be either −1 (a dead node), 0 (an inactive node), 1 (a non-cluster-head node) or 2 (a cluster head node).$E_{s_i,\ s_j}$ is the energy consumption for transmitting data from node s_i to s_j, which is defined in Eq. (6).

$$E_{s_i,s_j} = \begin{cases} E_{elec} \times l + E_{fs} \times l \times d^2{}_{s_i,s_j} & if \quad d_{s_i,s_j} < d_0 \\ E_{elec} \times l + E_{mp} \times l \times d^4{}_{s_i,s_j} & if \quad d_{s_i,s_j} \ge d_0 \end{cases} \tag{6}$$

E_{elec} is the energy consumed by the transceiver circuit. E_{fs} and E_{mp} are the energy expenditures for transmitting l-bit data to achieve an acceptable bit error rate, for the free space model and the multipath fading model [16], respectively. If the distance d_{s_i,s_j} between two sensor nodes is less than the threshold $d_0 = \sqrt{E_{fs}/E_{mp}}$, the free space model is applied, otherwise, the multipath model is used.

E_{RX} and E_{DA} are the energy consumed for receiving and aggregating data which are computed in Eq. (7).

$$E_{RX} = E_{DA} = E_{elec} \times l \tag{7}$$

The total energy consumed for activating all nodes at the current round, namely E_{total}, which is defined in Eq. (8).

$$E_{\mathrm{total}} = \sum_{i=1}^{n} E_{AC} \times a_i \tag{8}$$

Where E_{AC} is the energy consumed by activating an inactive node, a_i indicates whether the sensor node s_i is active or not, which is defined in Eq. (9).

$$a_i = \begin{cases} 1 & if\ s_i \in S_{nonCH}\ or\ \in S_{CH} \\ 0 & otherwise \end{cases} \tag{9}$$

1) The Coverage Rate

Coverage rate should be maintained to a high level in WSN. In this paper, we convert the problem of maximizing the coverage rate into minimizing the number of uncovered target points $N(I)$ defined in Eq. (10).

$$N(I) = \sum_{i=1}^{M} U(s_t) \tag{10}$$

where

$$U(s_t) = \begin{cases} 0 & if\ \exists s_i \in S_{active}\ \ and\ \ d(s_i, s_t) \le r_i \\ 1 & otherwise \end{cases} \tag{11}$$

$U(s_t)$ defined in Eq. (11) is used to determine whether the target point s_t is covered. M is the number of target points, S_{active} is the set of active sensor nodes.

1) The Energy Equilibrium

Definition 1. Regional energy

The monitoring area is divided into K grids, $k \in [1, ..., K]$. The regional energy in the k-th grid EQ_k defined in Eq. (12) equals to the average rest energy of all nodes in this grid.

$$EQ_k = \frac{\sum_{i=1}^{n_k} E_{k_i}}{n_k} \tag{12}$$

Where n_k is the number of nodes in the k-th grid, E_{k_i} is the rest energy of the i-th node in the k-th grid.

Definition 2. Energy Span

The energy span in the current network (the equilibrium degree of energy consumption in the whole network) $Es(I)$ defined in Eq. (13) can be represented by the ratio of the difference between the maximal and minimal regional energy to the maximum of the regional energy for solution I.

$$Es(I) = \frac{Max(EQ_k) - Min(EQ_k)}{Max(EQ_k)} \tag{13}$$

A smaller value of $Es(I)$ means the energy consumption in the network is more uniformly distributed.

Based on the definitions above, in order to achieve higher network coverage while effectively prolonging the network lifetime, we formally define the multi-objective coverage optimization problem of WSN with three objectives defined in Eq. (14)–(16) as follows:

1) f_1(I) *Minimize the number of uncovered targeting nodes*

$$f_1(I) = Min(N(I)) \tag{14}$$

1) f_2(I) *Minimize the energy consumption of the network*

$$f_2(I) = Min(E(I)) \tag{15}$$

1) f_3(I) *Minimize the energy span*

The third objective aims at preventing excessive energy consumption of sensor nodes in partial regions within the whole network as much as possible.

$$f_3(I) = Min(Es(I)) \tag{16}$$

3. Related works for the multi-objective coverage optimization problem

Zhang et al. [38] proposed the MOEA/D algorithm by decomposing a MOP into a number of single objective optimization problems (i.e. sub-problems), and optimizing them simultaneously. By using the optimization information of the neighboring sub-problem, the sub-problem will be optimized. The Tchebycheff Approach is used as a decomposition method in MOEA/D due to its ability to transfer the objective function of the i-th sub-problem using non-convex Pareto optimal front in Eq. (17) as follows:

$$\min g^{te}(x|\lambda^i, z*) = \max_{1 \le i \le m} \{\lambda_j^i |f_j(x) - z_j^*|\} \tag{17}$$

Where x denotes the decision variable space, $\lambda^i = (\lambda_1^i, ..., \lambda_m^i)^T$, λ^1, ..., λ^N denote a weight vector corresponding to the i-th sub-problem, $\forall j = 1, \ldots, m$, $\lambda_j \ge 0$ and $\lambda_1 +, ..., \lambda_m = 1$, m is the number of objective functions, $z* = (z_1^*, \ldots, \ z_m^*)^T$is the reference point. $z_j{}^*$ is the optimal value of the j-th objective function. In MOEA/D, a neighborhood of weight vector λ^i is defined as a set of its several closest weight vectors in $\{\lambda^1, \lambda^2, ..., \lambda^N\}$ .The neighborhood of the i-th sub-problem consists of all the sub-problems with the weight vectors from the neighborhood of λ^i.

Özdemir et al. [9] used MOEA/D to solve the problem of multi-objective coverage optimization in WSN, which can provide a better performance than the classical NSGA-II algorithm. Genetic algorithm is inspired by Darwin's theory of evolution, and a heuristic search algorithm is proposed based on the biological evolution process.

In [36], a WSN's energy-aware and coverage preserve hierarchal clustering and routing model based on multi-objective bat swarm optimization algorithm has been proposed, where two objectives including the coverage and nodes residual energies have been taken into consideration. The proposed model outperforms the LEACH routing and clustering protocol.

In [37], a demand-based coverage and connectivity-preserving routing protocol has been proposed to provide desired coverage and connectivity requirements in WSNs. Simulation results show that the proposed protocol effectively maintains the desired coverage and connectivity of the network and prolongs the network lifetime.

The differential evolution algorithm in Xu et al. [39] obtained a better performance than the classical NSGA-II algorithm on a two-objective coverage problem of WSN. Li et al. [40] proposed a multi-objective coverage optimization algorithm MOCADMA for WSN, which uses a memetic algorithm with a dynamic local search strategy to optimize multiple objectives including the network coverage, the node utilization and the residual energy. The experiment and evaluation results show that MOCADMA have good capabilities in maintaining the sensing coverage, achieving higher network coverage, and effectively prolonging the network lifetime compared with some existing algorithms.

4. The proposed hybrid-MOEA/D algorithms

In this paper, we proposed a hybrid MOEA/D algorithm based on the work in [9], namely Hybrid-MOEA/D-I, by combining Genetic Algorithm (GA) and Differential Evolution (DE) as the mixed reproduction operator to optimize each sub-problem.

In Hybrid-MOEA/D-I, the population $IP = \{I^1, I^2, \ldots, I^{pop}\}$ of *pop* individual solutions I is defined in Eq. (18), *pop* is the size of population, each as a fixed-length chromosome of size equal to the total number of nodes in WSN. I_j^i is the j-th gene (sensor node) of the i-th individual or chromosome with a value of either −1, 0, 1 or 2, where −1 means a dead node, 0 represents an inactive node in $S_{inactive}$, 1 means an active non-cluster-head node in S_{nonCH}, and 2 represents a cluster head node in S_{CH}, respectively. $E(s_j)$ is the remaining energy of the j-th sensor node.

$$I_j^i = \begin{cases} -1 & if \ \ E(s_j) = 0 \\ 0 & if \ \ E(s_j) > 0 \text{ and } s_j \in S_{inactive} \\ 1 & if \ \ E(s_j) > 0 \text{ and } s_j \in S_{nonCH} \\ 2 & if \ \ E(s_j) > 0 \text{ and } s_j \in S_{CH} \end{cases} \tag{18}$$

$\forall i \in \{1, \ldots., pop\} and \forall j \in \{1, \ldots., n\}$

The initial population is randomly generated. Each alive sensor node in the network becomes an active/inactive node with an equal

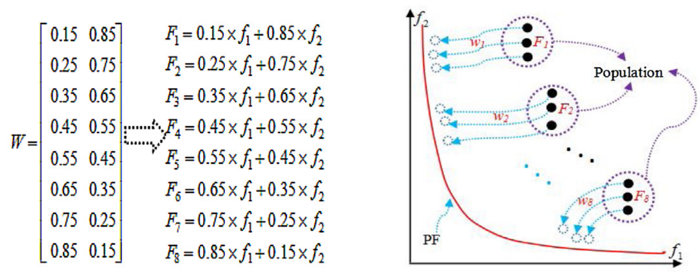


Fig. 3. An Example of Sub-problems. (a) Formula representation of sub-problems (b) Graphical representation of sub-problem.

probability (i.e. $p = 0.5$). An active node becomes a cluster head (CH) node with the probability defined in Eq. (19) as follows:

$$p_{opt}/(1-p_{opt}\times(r\bmod\frac{1}{p_{opt}})) \tag{19}$$

The optimal selection probability p_{opt} defined in LEACH is calculated as: $p_{opt} = K_{\mathrm{opt}}/n$, where n is the number of nodes in the network, r is the current round number, and K_{opt} is the optimal number of constructed clusters, $K_{opt}=\sqrt{\frac{n}{2\pi}}\frac{2}{0.765}$, as calculated in [16].

The population size *pop* is set as the same of the number of sub-problems N, each sub-problem composed of a weight vector and m objective functions. Take two objective functions as examples, in Fig. 3. f_1 (X axis) and f_2 (Y axis) represent two objective functions, F_γ are formulations of sub-problems, $\gamma \in [1,2,..,8]$. $W = \{w_1,\ldots,w_8\}$ is the weight vector matrix, the sum of all elements of each row is 1, the number of rows is equal to the number of sub-problems, and the number of columns is equal to the number of objectives. The same definition can be found in [35].

To improve the efficiency of search, some of the N sub-problems are optimized by GA and the others by DE. Using the best solutions generated by Hybrid-MOEA/D-I as the initial solutions, an improved algorithm called Hybrid-MOEA/D-II is proposed to integrate a discrete binary particle swarm optimization (DPSO).

4.1. The proposed hybrid-MOEA/D-I algorithm

To increase the population diversity, two different reproduction operators based on GA and DE have been designed in Hybrid-MOEA/D-I to optimize the N sub-problems. The mutation probability of DE and GA operator is p_{mDE} and p_{mGA}, respectively. The crossover probability of DE and GA operator is p_{crDE} and p_{crGA}, respectively. For $j \in [1, 2, .., m]$, f_j is the value of the j-th objective function. We assume z_j is the best value of the j-th objective function during the search, I^i is the current best solution for the i-th sub-problem in terms of all objectives, and $f_j(I^i)$ is the value of the j-th objective function for I^i. IP (Internal Population) is the population maintained during the search.

The GA and DE operators will be selected randomly for solving each sub-problem. The procedure of the hybrid GA-DE operator used in Hybrid-MOEA/D-I, shown in Algorithm 1.

1) The DE reproduction operator

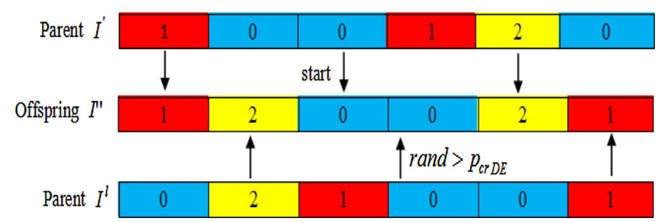


Fig. 4. The Crossover Operation Procedure of DE.

The DE operator includes three main procedures, i.e. the mutation, crossover and selection. Taking the l-th sub-problem as an example, the mutation operation of DE is defined based on Eq. (20):

$$I_r^{'}=\begin{cases}I_r^l+\eta\times(I_r^u-I_r^h) & r \quad and \ \le p_{mDE}\\ I_r^h & otherwise\end{cases} \tag{20}$$

I^l is the solution of the l-th sub-problem which has T neighboring sub-problems. I^u and I^h are two solutions of the u-th and h-th neighboring sub-problems of I^l, u and h are randomly selected indices from $[1,2, \ldots, T]$. $I^{'}$ is the new solution generated from I^l, I^u and I^h. I_r^l, I_r^u, I_r^h and $I_r^{'}$ represent the r-th gene of I^l, I^u, I^h and $I^{'}$, respectively, where $r \in [1,\ldots,n]$. The real-value constant η is a scaling factor. $p_{mDE} \in (0, 1)$ is the mutation probability. $rand \in (0, 1)$ is a random number.

The polynomial crossover generates $I^{''} = (I_1^{''}, I_2^{''}, \ldots, I_n^{''})$ from $I^{'}$ and I^l based on Eq. (21). $p_{crDE} \in (0, 1)$ is the crossover probability.

$$I_r^{''}=\begin{cases}I_r^{'} & r \quad and \ \le p_{crDE}\\ I_r^l & otherwise\end{cases} \qquad r\in[1,\ \ldots,\ n] \tag{21}$$

Fig. 4 shows a new offspring solution I'' generated based on parents $I^{'}$ and I^l. A gene in I'' is randomly selected from chromosome $I^{'}$ and then other genes of I'' are generated from either $I^{'}$ or I^l based on the crossover probability p_{crDE}.

1) The GA reproduction operator

The GA operator includes three main procedures, i.e. the selection, crossover and mutation. Two individuals I^l and I^u are used to generate a new solution I and $I^{'}$ based on a two-point crossover operation. To perform the mutation operation, a parent solution is randomly selected from I or $I^{'}$. Assuming $I^{'}$ is selected, a new solution I'' is generated based on the mutation operator as shown in

Table 1
The Mutation Operator of GA.

$I_r^{''}$	$I_r^{'}=0$		$I_r^{'}=1$		$I_r^{'}=2$	
	$rand \le P_{mGA}$	$rand > P_{mGA}$	$rand \le P_{mGA}$	$rand > P_{mGA}$	$rand \le P_{mGA}$	$rand > P_{mGA}$
	1	2	0	2	0	1

Table 1, where $I_r^{''}$ is the r-th gene of $I^{''} = (I_1^{''}, I_2^{''}, \ldots, I_n^{''})$ and $rand \in (0, 1)$ is a random number.

Two reproduction operators DE and GA have been randomly selected to optimize all sub-problems, aiming to diversify the search to obtain high-quality solutions. The pseudo code of Hybrid-MOEA/D-I is as shown in Algorithm 1.

	$I_r^{'}=0$		$I_r^{'}=1$		$I_r^{'}=2$	
$I_r^{''}$	$rand \le p_{mGA}$	$rand > p_{mGA}$	$rand \le p_{mGA}$	$rand > p_{mGA}$	$rand \le p_{mGA}$	$rand > p_{mGA}$
	1	2	0	2	0	1

4.2. The proposed hybrid-MOEA/D-II algorithm

In Hybrid-MOEA/D-I, the weights of each sub-problem are fixed, so the search direction is determined. To further improve the efficiency of the search, an improved Discrete Particle Swarm Optimization (DPSO) algorithm is adopted as the enhancement strategy to Hybrid-MOEA/D-I, leading to a new hybrid algorithm Hybrid-MOEA/D-II. As shown in Fig. 5, Hybrid-MOEA/D-I algorithm is used to optimize the initial solutions generated randomly, and DPSO is applied to further enhance the search.

Taking five sub-problems in Fig. 6 as an example, the solution of each sub-problem is optimized by a randomly selected optimization operator to generate a new solution. Then, the current solution and the neighborhood solution (the solution of neighbor sub-problem) are updated. A DPSO is then applied to further enhance the search.

Particle swarm optimization (PSO) concerns two important issues: exploration and exploitation. Exploration is obtained by particles' ability to change the original search trajectory to a new direction, i.e. to search the unexplored region in the search space. Exploitation is achieved by particles to search within the explored area. The relationship between exploration and exploitation is shown in Fig. 7(a). The moves of particles in DPSO are showed in Fig. 7(b). The velocity updating formula of discrete binary PSO algorithm proposed by Kennedy and Eberhart [41] is the same as that of the original PSO algorithm. Each individual is treated as a particle in the d dimensional search space. For the MCP in WSN, the

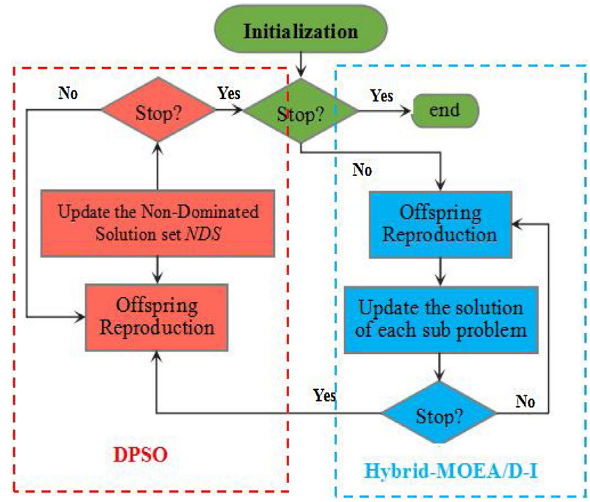


Fig. 5. The Hybridization of DPSO and Hybrid-MOEA/D-I.

best previous position of the i-th particle $I^i = \{I_1^i, I_2^i, \ldots, I_n^i\}$ is represented as $I^{i-best} = \{I_1^{i-best}, I_2^{i-best}, \ldots, I_n^{i-best}\}$. The global best solution among all particles in the population is represented as $I^g = \{I_1^g, I_2^g, \ldots, I_n^g\}$.

The position change velocity for particle i is defined as $V^i = \{V_1^i, V_2^i, \ldots, V_n^i\}$. Each particle updates each bit V_k^i of V^i according to Eq. (22).

$$V_k^i = \omega \times V_k^i + c_1 \times r_1 \times (I_k^{i-best} - I_k^i) + c_2 \times r_2 \times (I_k^g - I_k^i) \quad k \in (1, 2, \ldots, n) \tag{22}$$

In Eq. (22), ω, c_1 and c_2 are parameters in DPSO for velocity updating, r_1 and r_2 are random constants between 0 and 1. The velocity formula is consists of three items, the first item $\omega \times V_k^i$ is the inertial part; the second item $c_1 \times r_1 \times (I_k^{i-best} - I_k^i)$ is the local cognitive part; and the third item $c_2 \times r_2 \times (I_k^g - I_k^i)$ is the social cognitive part. In the improved DPSO, the value of I_k^i, I_k^{i-best} and I_k^g can only be 0 or 1. Since only a few cluster head nodes exist in WSN, I_k^i seldom takes value 2, so we ignore the case for $I_k^i = 2$. In other

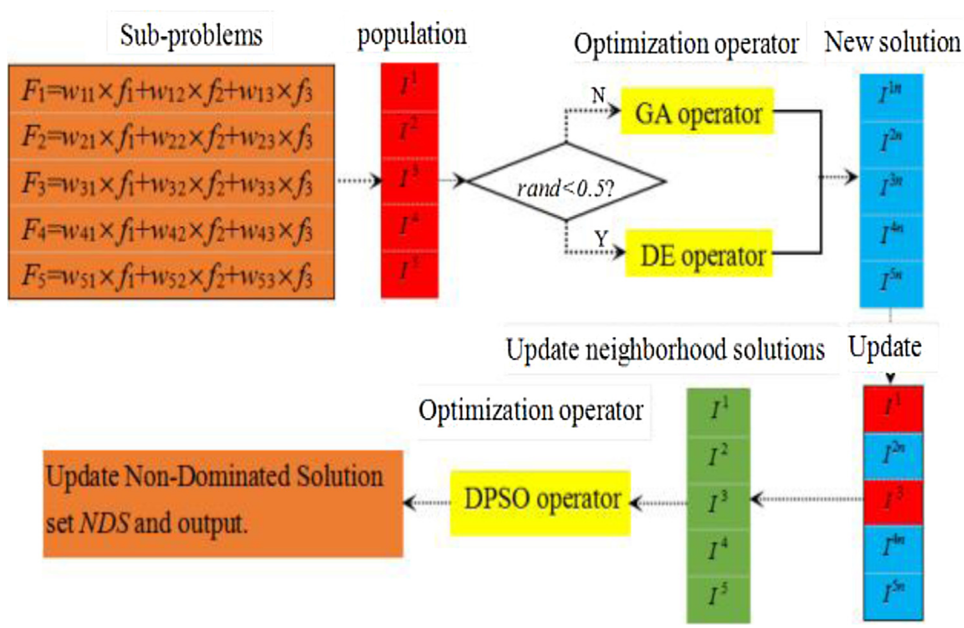
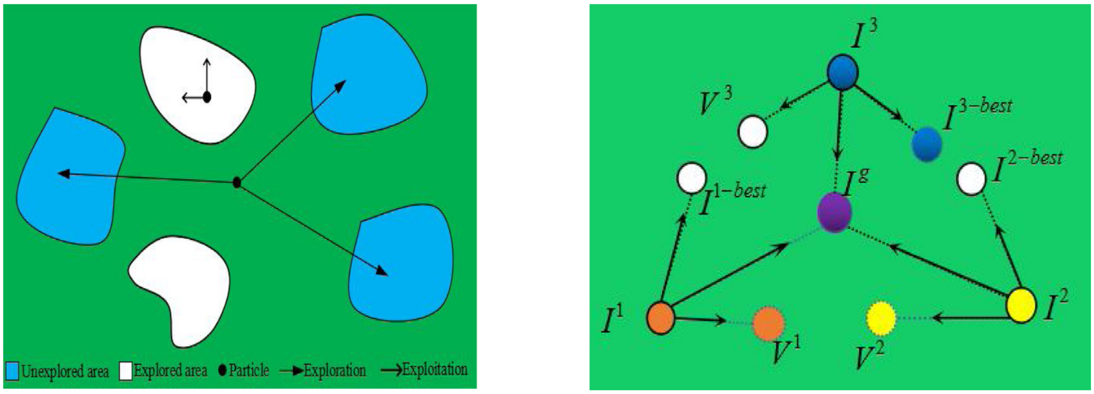


Fig. 6. An Example of the Framework of Hybrid-MOEA/D-II Algorithm.



(a) Particle exploration and exploitation (b) The Moves of Particles in PSO

Fig. 7. The Movements of Particle Swarm Optimization Algorithm. (a) Particle exploration and exploitation (b) The Moves of Particles in PSO.

Table 2
The relationship of I_k^i, I_k^{i-best} and I_k^g.

value	Possible values for I_k^i, I_k^g and I_k^{i-best}	How to change the value of I_k^i
1	I_k^{i-best} or I_k^g is 1, and the value of I_k^i is 0.	I_k^i needs to be changed to 1 with the most possibility.
0	I_k^{i-best} or I_k^g is equal to the value of I_k^i.	I_k^i should remain unchanged.
−1	I_k^{i-best} or I_k^g is 0, and the value of I_k^i is 1.	I_k^i needs to be changed to 0 with the most possibility.

words, the DPSO algorithm is used to schedule the active and non-active nodes in the case where the position and number of cluster heads are constant. $\left(I_k^{i-best} - I_k^i\right)$ and $\left(I_k^g - I_k^i\right)$ take values of −1, 0 or 1, and the relationship of I_k^{i-best}, I_k^i and I_k^g is shown in Table 2.

In other words, when V_k^i is 0, the value of the probability mapping function is 0; when V_k^i is less than 0 or greater than 0, the probability mapping function is an even function. When V_k^i tends to be positive or negative infinity, the probability mapping function value is 1. The probability mapping function is defined in Eq. (23) (see [12]):

$$p(V_k^i) = \begin{cases} 1 - \dfrac{2}{1+\exp(-V_k^i)} & when \quad V_k^i \le 0 \\ \dfrac{2}{1+\exp(-V_k^i)} - 1 & when \quad V_k^i > 0 \end{cases} \tag{23}$$

When the velocity V_k^i is negative, $p(V_k^i)$ decreases; otherwise, $p(V_k^i)$ increases; if $V_k^i = 0$, $p(V_k^i)$ is 0.

The position of a particle is defined in Eq. (24):

If $V_k^i < 0$

$$I_k^i = \begin{cases} 0 & if \quad r_1 \le \mathrm{p}(V_k^i) \text{ and } I_k^i \ne 2 \\ I_k^i & otherwise \end{cases} \tag{24}$$

If $V_k^i > 0$

$$I_k^i = \begin{cases} 1 & if \quad r_2 \le \mathrm{p}(V_k^i) \text{ and } I_k^i \ne 2 \\ I_k^i & otherwise \end{cases}$$

r_1 and r_2 are randomly generated from the uniform distribution of interval [0, 1].

The pseudo code of Hybrid-MOEA/D-II is as shown in Algorithm 2.

Algorithm 2 The framework of Hybrid-MOEA/D-II

Input:
- The output of Hybrid-MOEA/D-I IP = {I1, I2, …, Ipop};
- genmax: the maximum number of generations;

Output:
- The Non-Dominated Solution set *NDS*;

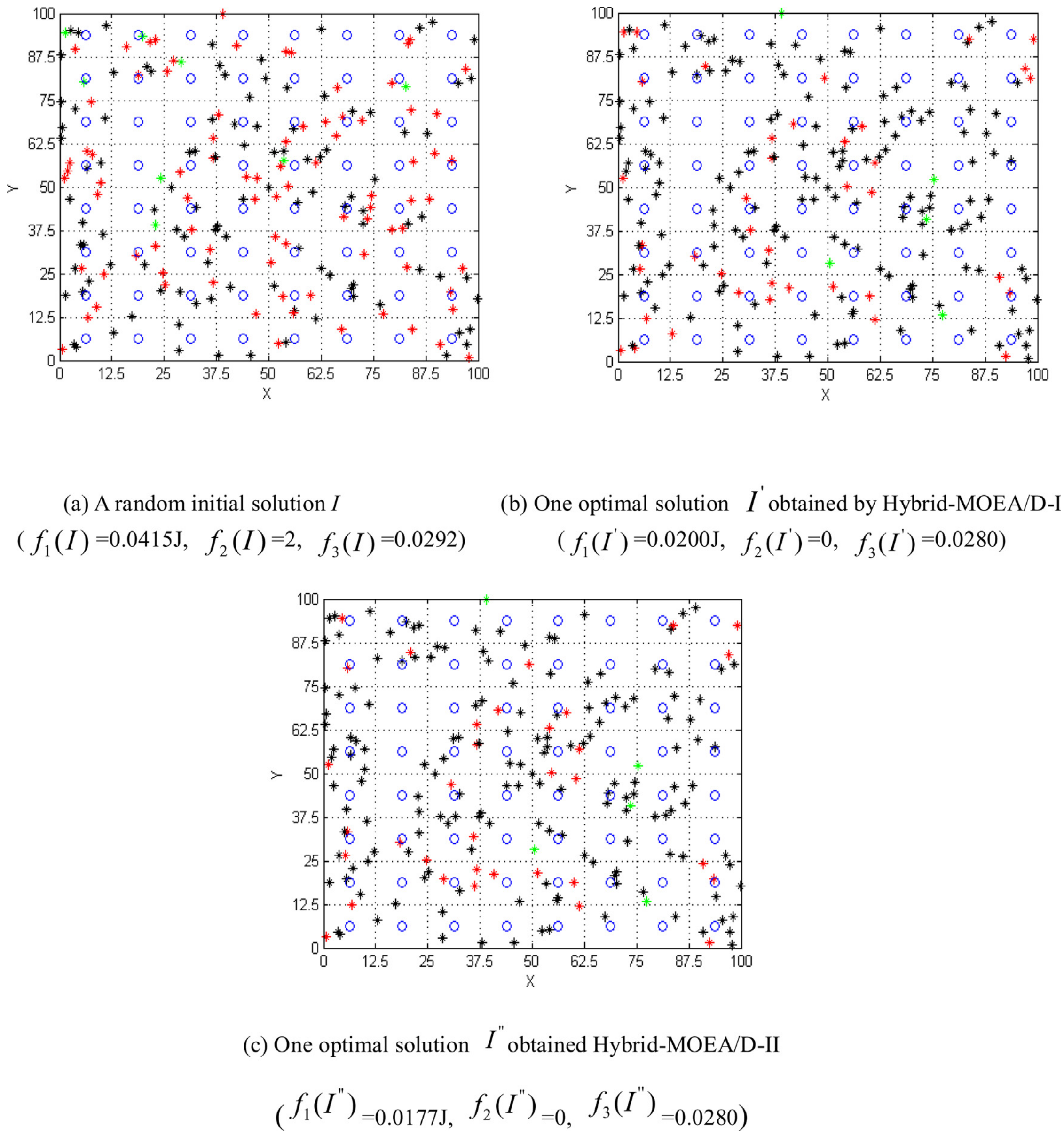
Step 1 - Initialization
1.1: **For** $i = 1, \ldots, pop$
1.2: Initialize the position of the *i*-th particle I^i, the *i*-th subproblem generated by Hybrid-MOEA/D-I.
1.3: The initial velocity of the *i*-th particle = 0;
1.4: **end For**
1.5: Updated the Non-Dominated Solution set *NDS*;
1.6: Choose the particle with the best objective function value of all
the particles as the global best;

Step2 - Update:For i=*1,…,N*
2.1: Update the velocity of each particle according to Eq. (22)
2.2: Update the position of each particle according to Eq. (24);
2.3: Calculate the value of the objective function for each particle based on the position of the particle;
2.4: Update the best and the global best;
2.5: Update the Non-Dominated Solution set *NDS*;
2.6: **endFor**

Step3 - Stopping criteria
3.1: **If** $gen == gen_{max}$ **then** stop and output *NDS*;
3.2: **else** $gen = gen + 1$, go to Step2;
3.3: **endIf**

4.3. An illustrative example of the proposed hybrid algorithms

In an illustrative example, assume the number of sensor nodes is 200, the number of target points is 64, and the initial energy of each sensor node is 0.02J. Fig. 8 presents and compares the solutions found by Hybrid-MOEA/D-I (see Fig. 8(a)) and Hybrid-MOEA/D-II (see Fig. 8(b)) with the same random initial solution showed in Fig. 8(a). For each solution, a black point represents a non-active node, a red point represents active non-cluster head nodes, and a green point indicates a cluster-head node. The values of the three objectives, i.e. $f_1(I)$ (the total energy consumption of each round); $f_2(I)$ (the number of uncovered target points); $f_3(I)$ (the energy span), are shown below each solution.



(a) A random initial solution I

$(f_1(I)=0.0415\text{J},\ f_2(I)=2,\ f_3(I)=0.0292)$

(b) One optimal solution I' obtained by Hybrid-MOEA/D-I

$(f_1(I')=0.0200\text{J},\ f_2(I')=0,\ f_3(I')=0.0280)$

(c) One optimal solution I'' obtained Hybrid-MOEA/D-II

$(f_1(I'')=0.0177\text{J},\ f_2(I'')=0,\ f_3(I'')=0.0280)$

Fig. 8. Comparison of Solutions found by Hybrid-MOEA/D-I and Hybrid-MOEA/D-II. (a) A random initial solution I. (b) One optimal solution I' obtained by Hybrid-MOEA/D-I. $(f_1(I)=0.0415\text{J}, f_2(I)=2, f_3(I)=0.0292)$ $(f_1(I')=0.0200\text{J}, f_2(I')=0, f_3(I')=0.0280)$. (c) One optimal solution I'' obtained Hybrid-MOEA/D-II. $(f_1(I'')=0.0177\text{J}, f_2(I'')=0, f_3(I'')=0.0280)$.

For the random initial solution I, the number of non-active nodes is 105, the number of non-cluster-head nodes is 85, and the number of cluster head nodes is 10. For the solution I' obtained by Hybrid-MOEA/D-I, the number of non-active nodes is 156, the number of non-cluster-head nodes is 39, and the number of cluster-head nodes is 5. Comparing the two solutions I and I', we can see that the solution obtained by Hybrid-MOEA/D-I has a better coverage (the uncovered node number $f_2(I')=0<f_2(I)=2$) with less energy consumption $(f_1(I')=0.0200\text{J}<f_1(I)=0.0415\text{J})$ and slightly better energy span $(f_3(I')=0.0280<f_3(I)=0.0292)$. One non-dominated solution obtained by the DPSO enhancement strategy is Hybrid-MOEA/D-II is shown in Fig. 8(c). The number of non-active nodes is 161, the number of non-cluster-head nodes is 34, and the number of cluster head nodes is 5. It can be seen that Hybrid-MOEA/D-II further enhances the search and obtains a better solution I'' with less energy $(f_1(I'')=0.0177\text{J} <f_1(I')=0.0200\text{J})$ compared with the solution I' generated by Hybrid-MOEA/D-I with the same coverage rate and energy span.

4.4. The time complexity analysis

We firstly analyze the time complexity of MOEA/D-PSO in the literature [11] as follows. MOEA/D-PSO applied a PSO algorithm in MOEA/D to solve the coverage optimization problem in WSN with two optimization objectives including the coverage rate and the network lifetime.

1) The population size is N, i.e. N sub-problems, each sub-problem has g number of iterations, each individual is represented as a fixed-length chromosome with size equal to n, i.e. the total number of nodes in WSN;
2) The GA operator: two point crossover and mutation operate on each gene in the chromosome, in the worst case, mutation and crossover operations need to be performed on n genes, requiring $g\times N\times n$ operations;
3) The PSO operator: the main steps of PSO include updating the velocity, the position, the personal best and the global best,

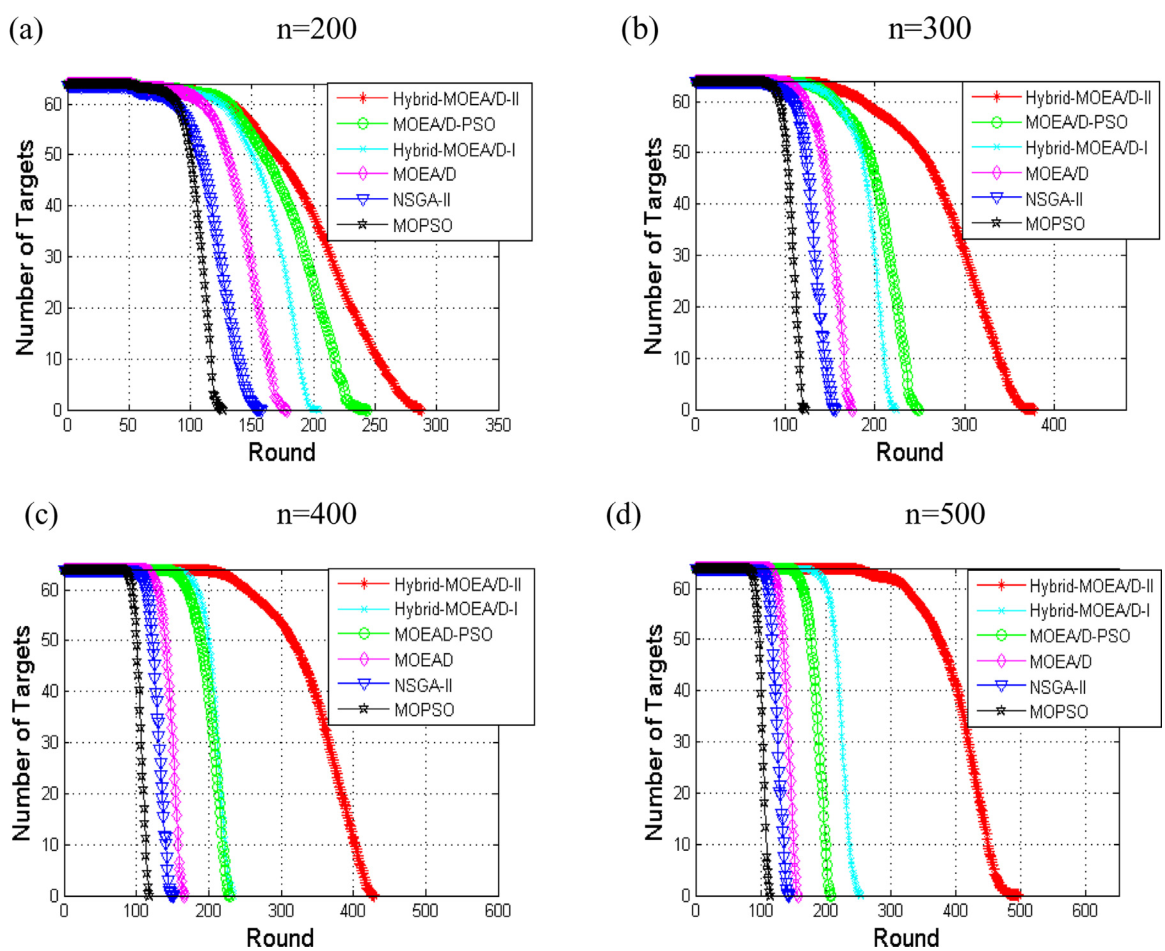


Fig. 9. The comparison of total number targets detected.

requiring $g \times N \times n$, $g \times N \times n$, $g \times N$ and $g \times N$ operations, respectively;

4) Each sub-problem updates the reference point and the neighborhood solutions, requiring $g \times N$ operations, respectively.

The time complexity of the MOEA/D-PSO algorithm is:

$$O(\text{MOEA/D-PSO}) = g \times (2 \times N \times n + 2 \times N \times n + 2 \times N + 2 \times N) = 4 \times g \times N \times (n+1),$$

So the time complexity of MOEA/D-PSO is $O(g \times N \times n)$.

The basic idea of MOEA/D is to decompose a MOP into a set of single-objective optimization problems and optimize them simultaneously. We analyze the time complexity of Hybrid-MOEA/D-I as follows.

1) The population includes N particles (sub-problems), each has g iterations. Each individual is represented as a fixed-length chromosome of size n, where n is the total number of nodes in WSN;
2) The DE operator is applied to half of the population, and is consists of the mutation and crossover operations. In the worst case, n genes are applied mutation and crossover, so leading to $0.5 \times g \times N \times n$ operations, respectively;
3) The GA operator is applied to half of the population, which includes the crossover and mutation operations. In the worst case, this requires $0.5 \times g \times N \times n$ mutation and crossover operations, respectively, applied to n genes;
4) Each solution of sub-problem needs to update reference point and update the neighborhood solutions, leading to $g \times N$ operations, respectively;

The time complexity of the Hybrid-MOEA/D-I algorithm is $O(\text{Hybrid-MOE/D-I}) = g \times (2 \times 0.5 \times N \times n + 2 \times 0.5 \times N \times n + 2 \times N) = 2 \times g \times N \times (n+1)$, so its time complexity of Hybrid-MOE/D-I is $O(g \times N \times n)$.

The main procedure of DPSO in Hybrid-MOEA/D-II is to update the particle velocity and particle position based on the solutions obtained by Hybrid-MOEA/D-I. The time complexity of Hybrid-MOEA/D-II is thus as follows.

1) The population size is N, i.e N particles, each of g iterations. Each individual has a fixed size n.
2) According to the velocity and the position update formula in Eq. (22) and Eq. (24), the velocity and positon of each particle is updated. The length of the chromosome of each particle is n, so these $g \times N \times n$ operations, respectively;
3) To update the personal best of each particle and the global best, $g \times N$ these operations are required, respectively;

The time complexity of Hybrid-MOEA/D-II is thus calculated as:

$$O(\text{Hybrid-MOEA/D-II}) = g \times (2 \times n \times N + 2 \times N) + O(\text{Hybrid-MOEA/D-I}) = 4 \times g \times N \times (n+1).$$

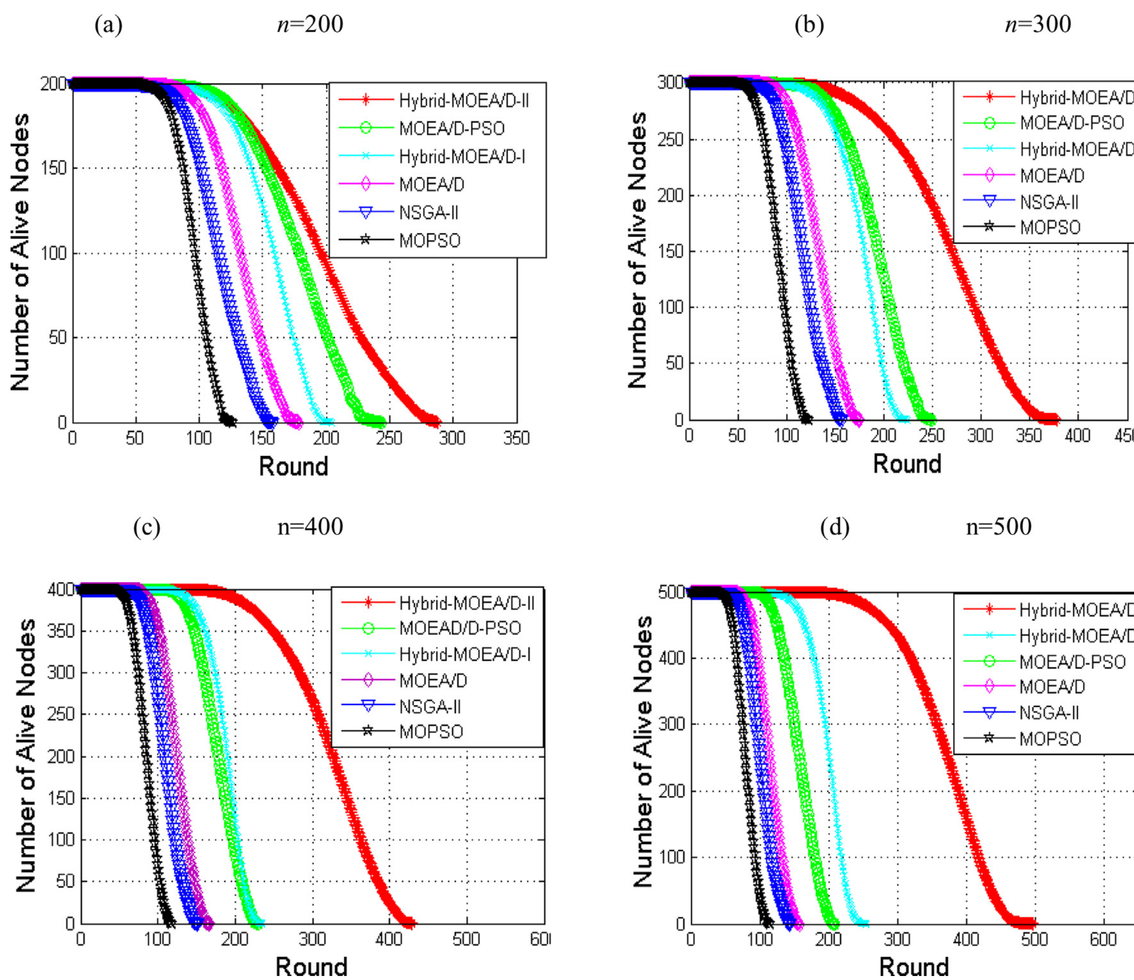


Fig. 10. The comparison of number of alive nodes in each round.

Table 3
Parameters used in simulations.

Parameter	Value	Parameter	Value
Network size: *n*	≤500	p_{crGA}	0.8
Targe area	100m × 100 m	p_{mGA}	0.03
Number of grids	64	p_{crDE}	0.9
Number of target points	64	p_{mDE}	0.7
Maximum iterations	≤8000	E_{elec}	50 nJ/bit
Maximum ideal sensing radius: r_i 10 m		ε_{fs}	100 pJ/bit/m^2
Node initial energy: E_0	0.02 J	E_{DA}	5 nJ/bit
The number of sub-problems *N*	50	ω	0.5
T	*10*	c_1	1
ε_{amp}	0.0013 pJ/bit/m^4	c_2	2

Thus the time complexity of Hybrid-MOEA/D-II is $O(g \times N \times n)$.

The above analysis indicates that the proposed Hybrid-MOEA/D-I and Hybrid-MOEA/D-II algorithms have the same time complexity as that of MOEA/D-PSO, showing that Hybrid-MOEA/D-I and Hybrid-MOEA/D-II can obtain better solutions without increasing the time complexity.

5. Performance comparison of different algorithms

In this paper, all algorithms are implemented using MATLAB. To evaluate the performance of Hybrid-MOEA/D-I and Hybrid-MOEA/D-II, simulation results are compared to those of MOPSO, NSGA-II, MOEA/D and MOEA/D-PSO using the same machine and parameters. The experimental parameters are shown in Table 3.

We compare the performance of our proposed two algorithms, i.e. Hybrid-MOEA/D-I and Hybrid-MOEA/D-II, with other four algorithms, including MOPSO, NSGA-II, MOEA/D and MOEAD-PSO for WSN with different number of sensor nodes (200, 300, 400 and 500 nodes, respectively). For each size of WSN, 10 topologies have been randomly generated and 20 independent runs of each algorithm have been repeated on each network topology.

We firstly compare the number of targets detected, the number of alive nodes and the remaining energy of each round. Each round includes a number of iterations of the algorithm (here we set the number of iterations as 20) to output the non-dominated solution set (*NDS*) and select a deployment solution. Then, we compare the coverage rate and energy consumption rate of different algorithms. We also compare the three objectives of *NDS* obtained by

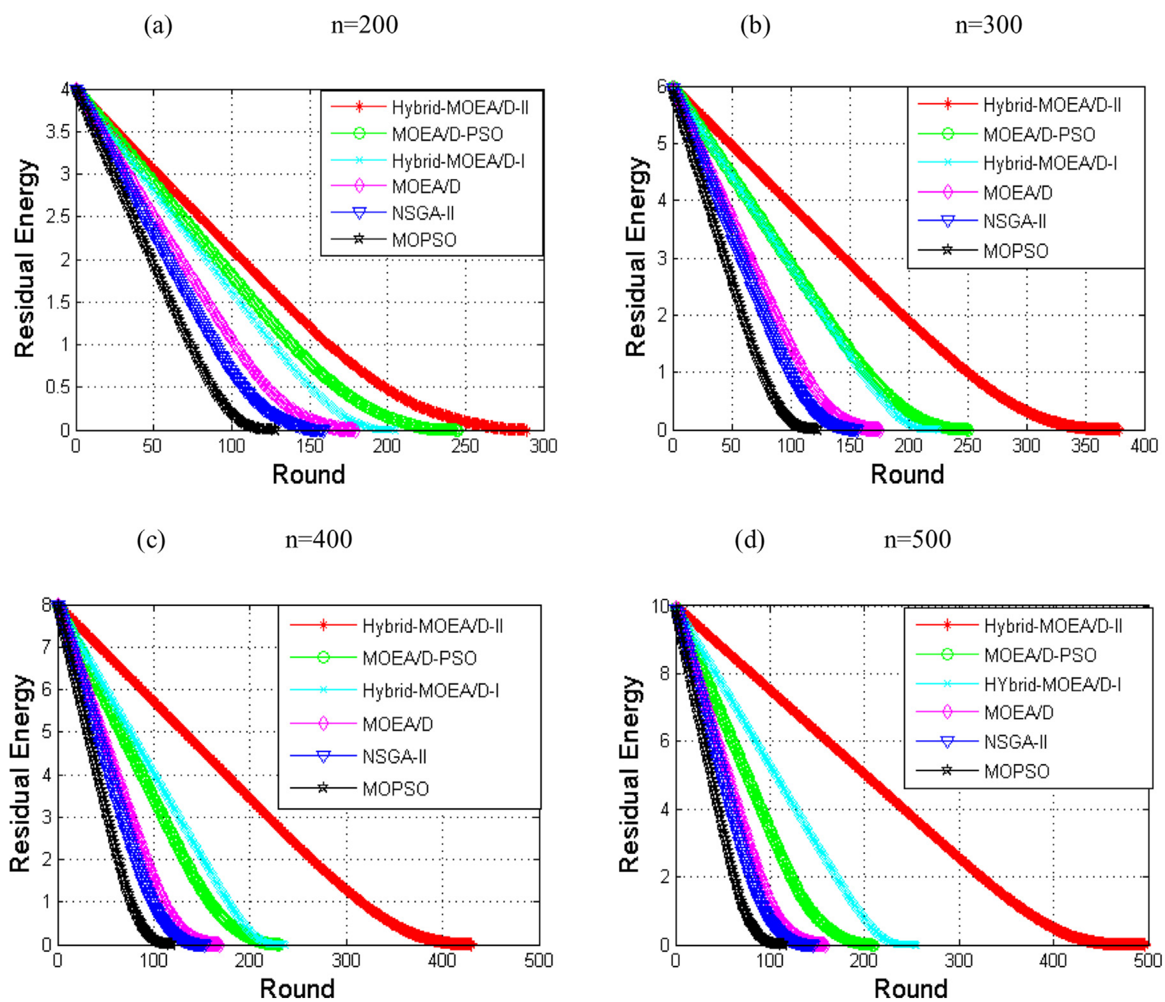


Fig. 11. The comparison of residual energy.

different algorithms. Moreover, to evaluate the solutions set of each algorithm, we used the Set Coverage metric (C-metric) [42] as the evaluation criteria. For two *NDS* sets *A* and *B*, C-metric is defined as: $C(A, B) = |b \in B| \exists a \in A : a \succ b|/|B|$, here *b* is a solution in *B* and *a* is a solution in *A*. Note that $C(A, B) \neq 1 - C(B, A)$, and *A* is better than *B*, if $C(A, B)$ is higher than $C(B, A)$ over many test. C-metric calculates the fraction of solutions in the *NDS* obtained by one algorithm which are dominated by the *NDS* obtained by another algorithm. Finally, we compare the running time and the *NDS* obtained at the tenth round of each algorithm.

5.1. The comparison of total number targets detected

In Fig. 9, the number of target points of six algorithms i.e., MOPSO, NSGA-II, MOEA/D, Hybrid-MOEA/D-I, MOEA/D-PSO and Hybrid-MOEA/D-II, are compared for WSN with different number of nodes. Compared with other algorithms, the deployment solution can be obtained by the Hybrid-MOEA/D-II algorithm can make the network in each round consumes less energy, higher coverage and more balanced network energy consumption, so we can see that for larger networks, Hybrid-MOEA/D-II obtained better performance (Under the premise of ensuring coverage, the network lifetime is prolonged). For $n = 200$ and $n = 300$, Hybrid-MOEA/D-I performs slightly worse than MOEA/D-PSO. For $n = 400$, Hybrid-MOEA/D-I and MOEA/D-PSO have the similar performance. For $n = 500$, Hybrid-MOEA/D-I is obviously better than the performance of MOEA/D-PSO algorithm.

5.2. The comparison of the number of alive nodes

Fig. 10 compares the performance of all six algorithms in terms of the number of sensor nodes alive for WSN with different number of sensor nodes. Compared with other algorithms, the deployment solution can be obtained by the Hybrid-MOEA/D-II algorithm can make the network in each round consumes less energy, So it is obvious that more surviving nodes have been obtained by Hybrid-MOEA/D-II for wireless sensor networks with different networks sizes during each round, prolonging network life time by saving more node energy.

5.3. The comparison of the remaining energy

In Fig. 11, the residual energy of sensor nodes of different algorithms is compared for WSN with different number of nodes. It shows again that more residual energy has been retained by Hybrid-MOEA/D-II for WSN during each round. This is clearer for WSN with more nodes.

5.4. The comparison of coverage rate and energy consumption rate

Fig. 12 compares the coverage rate and energy consumption of sensor nodes of six algorithms. Our proposed Hybrid-MOEA/D-II algorithm again has a higher coverage rate and lower energy con-

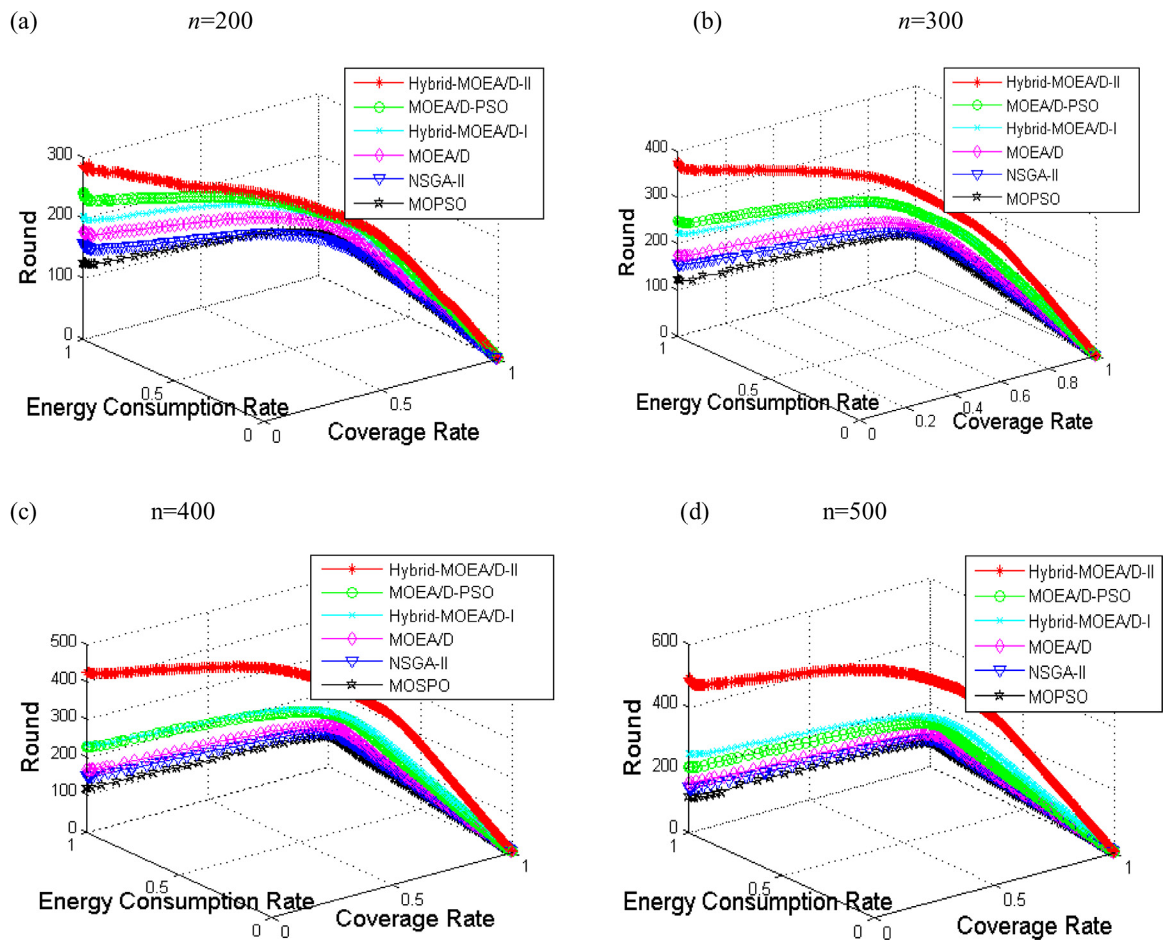


Fig. 12. The comparison of coverage rate and energy consumption rate.

sumption rate for wireless sensor networks with different number of nodes.

5.5. The comparison of non-dominated solution sets

In Fig. 13, the non-dominated solution sets within the tenth rounds of six different algorithms are compared on WSN with different number of nodes. Hybrid-MOEA/D-I and Hybrid-MOEA/D-II perform better than other four algorithms by obtaining better Pareto fronts with respect to the three objectives defined in Section 2. Better *NDS* sets have been obtained by Hybrid-MOEA/D-II compared with Hybrid-MOEA/D-I for four different sizes of WSN, which demonstrate the effectiveness of the DPSO enhancement strategy.

5.6. The comparison of set coverage metric

Tables 4 and 5 compare C-metric of our proposed hybrid algorithms with MOEAD-PSO, MOEA/D and NSGA-II for WSN with n = 200, 300, 400 and 500 nodes in the network at each round. Table 4 presents the values of C-metric of three algorithms, i.e., Hybrid-MOEA/D-I, MOEA/D and NSGA-II. The experiments show that all C-metric values of Hybrid-MOEA/D-I (I) are larger than the those of MOEA/D(II) and NSGA-II(III), which means Hybrid-MOEA/D-I has the best performance among the three algorithms. For example, for n = 200, at round = 25, all C(I, II) are larger than C(II, I), which means non-dominated solutions generated by Hybrid-MOEA/D-I dominate all those generated by MOEA/D. There is only one exception, for n = 300, at round 125, the C-metric value of C(I, II) is slightly larger than C(II, I). This means that the non-dominated

Table 4
Domination of Hybrid-MOEA/D-I(I) versus MOEA/D(II) and NSGA-II(III).

Round	C(I,II)	C(II,I)	C(I,III)	C(III,I)
n = 200				
1	**1**	0	**1**	0
25	**1**	0	**1**	0
50	**0.66**	0.06	**1**	0
75	**0.625**	0	**0.7**	0
100	**0.75**	0	**0.9**	0
125	**0.667**	0.111	**0.16**	0
n = 300				
1	**1**	0	**1**	0
25	**1**	0	**1**	0
50	**1**	0	**1**	0
75	**1**	0	**1**	0
100	**1**	0	**1**	0
125	**0**	0.051	**0**	0
n = 400				
1	**1**	0	**1**	0
25	**1**	0	**1**	0
50	**1**	0	**1**	0
75	**1**	0	**1**	0
100	**1**	0	**1**	0
125	**0.5**	0.4	**0**	0
n = 500				
1	**1**	0	**1**	0
25	**1**	0	**1**	0
50	**1**	0	**1**	0
75	**1**	0	**1**	0
100	**1**	0	**1**	0
125	**1**	0.050	**1**	0

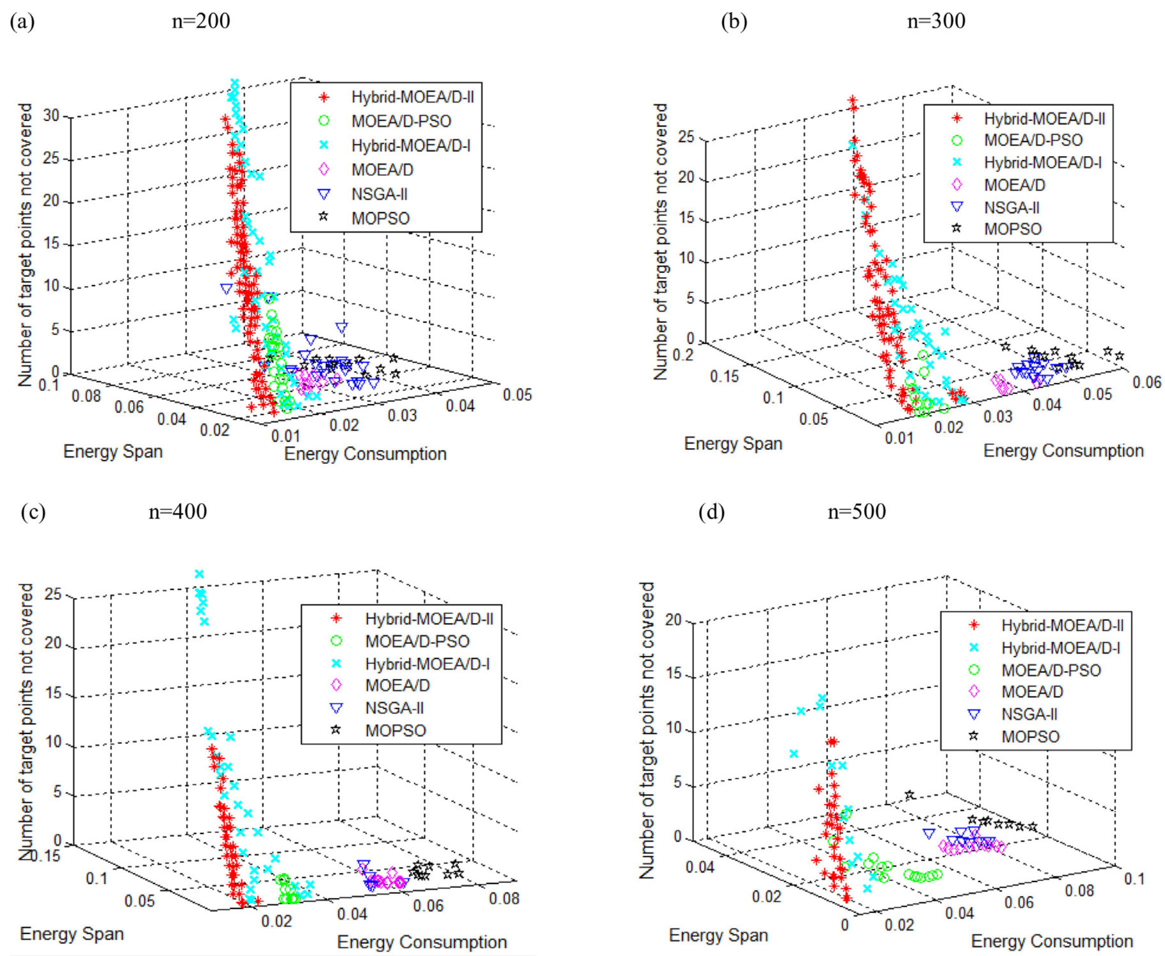


Fig. 13. The comparison of non-dominated solutions.

solution set found by MOEA/D at this round has a better diversity than that of Hybrid-MOEA/D-I. However, from Fig. 12(b), we c'an see that at round 125, the Coverage rate and Energy Consumption rate of Hybrid-MOEA/D-I are much better than those of MOEA/D.

Table V shows the comparison of the C-metric of Hybrid-MOEA/D-II, MOEA/D-PSO and Hybrid-MOEA/D-I with different network sizes at each round. For example, for $n = 200$, the non-dominated solutions generated by Hybrid-MOEA/D-II dominate 34.2% of those generated by MOEA/D-PSO at round 75, but the non-dominated solutions generated by MOEA/D-PSO algorithm dominate none of those generated by Hybrid-MOEA/D-II. When n becomes larger, Hybrid-MOEA/D-II obtained even better performance.

5.7. The comparison of running time

In Table 6, the running time of these six algorithms is compared after 10 rounds. Although the running time of Hybrid-MOEA/D-II is slightly longer than that of other algorithms, it always obtains much better results.

6. Conclusion

The issues of reducing and balancing the energy consumption while retaining high coverage rate represent conflicting objectives for WSN. In this paper, we model the coverage control problem in WSN as a MOP problem by considering three objectives, including the coverage rate, the energy consumption and the energy consumption equilibrium. A Hybrid-MOEA/D-I algorithm has been proposed based on the well-known MOEA/D algorithm. To increase population diversity, hybrid GA and DE reproduction operators have been applied in Hybrid-MOEA/D-I. This shows Hybrid-MOEA/D-I achieves a higher quality solution than MOEA/D.

In Hybrid-MOEA/D-I, each objective is optimized by a randomly generated weight, and the search direction is thus determined with the fixed weights. To further enhance the search ability of Hybrid-MOEA/D-I and preserve high quality individuals in each generation, we propose a new Hybrid-MOEA/D-II algorithm by introducing a discrete binary particle swarm optimization algorithm (DPSO) as the enhancement strategy to obtain better Pareto solution set.

We also analyze the time complexity of our proposed Hybrid-MOEA/D-I and Hybrid-MOEA/D-II as well as MOEA/D-PSO in the literature, and demonstrate that our proposed algorithms have a similar time complexity with that of MOEA/D-PSO.

Experimental results show that both the Hybrid-MOEA/D-I and Hybrid-MOEA/D-II perform significantly better than those of MOEA/D, NSGA − II, MOPSO and MOEA/D-PSO without increasing the time complexity. With DPSO as the further enhancement strategy, Hybrid-MOEA/D-II obtained much better performance than that of Hybrid-MOEA/D-I. The comparisons using the C-metric demonstrate that both the hybrid reproduction operator and the DPSO enhancement strategy have the ability to get better solution. In our future work, we plan to apply learning strategies to further improve the performance of our proposed algorithms. In addition,

Table 5
Domination of Hybrid-MOEA/D-II(IV) versus MOEA/D-PSO(V) and Hybrid-MOEA/D-I(I).

Round	C(IV,V)	C(V,IV)	C(IV,I)	C(I,IV)
$n = 200$				
1	**1**	0	**0.989**	0
25	**0.45**	0.305	**1**	0
50	**1**	0	**0.990**	0
75	**0.342**	0.15	**1**	0
100	**0.48**	0	**0.527**	0
125	**0.659**	0.0449	**0.778**	0
150	**0.5**	0.0185	**0.857**	0
$n = 300$				
1	**0.864**	0.042	**1**	0
25	**0.786**	0	**1**	0
50	**1**	0	**1**	0
75	**0.75**	0	**0.531**	0
100	**1**	0	**0.545**	0
125	**1**	0	**0.532**	0
150	**0.64**	0	**1**	0
$n = 400$				
1	**1**	0	**0.889**	0
25	**1**	0	**1**	0
50	**1**	0	**1**	0
75	**1**	0	**1**	0
100	**1**	0	**1**	0
125	**1**	0	**1**	0
150	**1**	0	**1**	0
$n = 500$				
1	**1**	0	**1**	0
25	**1**	0	**1**	0
50	**1**	0	**1**	0
75	**1**	0	**1**	0
100	**1**	0	**1**	0
125	**1**	0	**1**	0
150	**1**	0	**1**	0

Table 6
The comparison of running time of each algorithm.

Algorithm	n			
	200	300	400	500
Hybrid-MOEA/D-II	33.1s	48.4s	64.3s	79.6s
MOEA/D-PSO	27.1s	42.7s	53.8s	71.4s
Hybrid-MOEA/D-I	20.9s	30.8s	40.2s	50.6s
MOEA/D	17.5s	28.1s	34.8s	44.5s
NSGA-II	11.5s	15.8s	21.2s	26.5s
MOPSO	19.0s	28.4s	37.7s	49.4s

we plan to consider the coverage problem of WSN within more complex real world scenarios, such as those with mobile charger nodes in the networks.

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